A ROBUST SCALABLE TRANSPORTATION SYSTEM CONCEPT

FINAL REPORT
FOR
2005 REVOLUTIONARY SYSTEM CONCEPT FOR AERONAUTICS (RSCA) PROJECT

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Executive Summary

This report documents the 2005 Revolutionary System Concept for Aeronautics (RSCA) study entitled "A Robust, Scalable Transportation System Concept". The objective of the study was to generate, at a high-level of abstraction, characteristics of a new concept for the National Airspace System, or the "new NAS", under which transportation goals such as increased throughput, delay reduction, and improved robustness could be realized. Since such an objective can be overwhelmingly complex if pursued at the lowest levels of detail, instead a System-of-Systems (SoS) approach was adopted to model alternative air transportation architectures at a high level. The SoS approach allows the consideration of not only the technical aspects of the NAS, but also incorporates policy, socio-economic, and alternative transportation system considerations into one architecture. While the representations of the individual systems are basic, the higher level approach allows for ways to optimize the SoS at the network level, determining the best topology (i.e. configuration of nodes and links). The final product (concept) is a set of rules of behavior and network structure that not only satisfies national transportation goals, but represents the high impact rules that accomplish those goals by getting the agents to "do the right thing" naturally.

The novel combination of Agent Based Modeling and Network Theory provides the core analysis methodology in the System-of-Systems approach. Our method of approach is non-deterministic which means, fundamentally, it asks and answers different questions than deterministic models. The non-deterministic method is necessary primarily due to our marriage of human systems with technological ones in a partially unknown set of future worlds. Our goal is to understand and simulate how the SoS, human and technological components combined, evolve. The simulation was instantiated through significant use of actual data from today's transportation system obtained from the Bureau of Transportation Statistics (BTS). Once initialized, a validation exercise was performed and confirmed that the simulation could represent the reality of today's system, within the bounds on fidelity. Overall, this RSCA study shed new light not only on ideas for a "new NAS", but also on the potential of this new non-deterministic approach as well as its ability to point in the direction of a combination of technology development coupled with regulation and economic incentives that yield high payoff at low penalty. While the initial results are limited by the simplistic characterizations of the individual systems, it is expandable to greater detail or even wider breadth now that a study architecture baseline has been established.

Two concepts are produced using the SoS approach and are described in this RSCA study report. The first uncovers a particular pattern in the behavior associated with managing capacity of the NAS network. Specifically, the effectiveness of avoiding saturation and thus delay in the NAS is dependent on both the amount of capacity increment added and the speed at which this action can be implemented. The concept, then, is one of a flexible and intelligent capacity management. The second concept explores behavior patterns in service providers and uncovers situations in which the overall capacity network can be enhanced by a correlation between actions of regional and longer-distance service providers. In both cases, of course, additional scenarios need to be run to confirm that observed patterns are indeed pervasive, and thus robust. However, these pilot results are indeed illuminating.

A professional animation has been produced by animators at NASA Langley Research Center. The animation explains both the impact of the revolutionary concept and the essential elements of the new System-of-Systems analysis method. Those wishing to obtain a copy of the animation (in .mov format) can contact the authors of this report.

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I. Introduction

A. What are we investigating and why?

The concepts developed in this study are high-level, integrated transportation concepts (not individual aircraft), representing a vision of how better organization and operation in a "New NAS" could be possible. The motivation for this study centers around the desire to better understand possible ways in which the U.S. air transportation system might be transformed. Transformation is quite simply a decision-making problem and, thus, appropriate models are needed. Our prior work has established that the entire National Transportation System (NTS) is a System-of-Systems (SoS), within which are a variety of networks consisting of both individuals/organizations (sentience) and resources. Therefore, studies of transformation must link together not only the technical aspects of the NAS, but the political, socio-economic, and alternative transportation systems into one architecture. The presence of multiple, independent, sentient entities, however, makes transformation difficult- there is no central design authority. Under this setting, we must look at the NTS with a holistic perspective. The main goal of this research is to find a model for the NAS that is robust and scalable. However, there is one major difference between this and most other projects. In the majority of research a prediction is made but often not tested against external factors and feedbacks that occur over time in a dynamic system. Here, the goal is to allow a NAS to emerge over time. It is not expected that one "optimal" NTS exists, but it is expected that noticeable and important patterns will emerge.

The expected payoffs for NASA through execution of this RSCA study are twofold. First, the results can provide broad guidance for technology investment and regulation of the complex SoS that is the NAS. Second, the intellectual approach and the simulation capability developed can provide a means to understand and continually reassess NAS as new situations arise.

B. How do we plan to do this?

Investigating the "whole NAS" is very difficult, and thus most revolutionary concept studies center on individual systems: a new aircraft concept, a new air traffic management tool, etc. As a consequence, existing models for system analysis are very much focused on *static predictions for individual systems*. In contrast, a SoS concept cannot by modeled via static prediction, but instead must account for behaviors, technologies, and disruptions that may emerge over time. Thus, this study employs an analysis approach tailored for SoS problems. By abstracting the transportation "enterprise", we can identify inherent structures that can help us deal with this difficult problem. Upon completing an abstraction of a SoS, the concept of a network enters the forefront. If we can study the relationship between network topologies and key performance metrics, then we can use those topologies as targets for design. Likewise, the role of economics and policy are to shape the networks according to the objectives of some individual or group. Thus, we would like to include these shapers and determine the conditions under which their natural actions can also lead to preferred behavior at the global level. Network Theory allows us to understand and measure the goodness of the topology of the various networks while ABM provides a more realistic look at how the networks might evolve naturally and whether good is reachable (under what circumstances). Overall, representations of the individual systems will be very simplistic, the non-deterministic ABM allows for mimic of the real world uncertainty, and the manner in which the simulation is built means that more effects can be added in future.

C. What do we hope to find? What is our concept?

Our concepts consist of rules of behavior and network patterns that lead to scalability in the metrics that matter most in the NAS: delay reduction, increased throughput, and enhanced robustness. Thus, our concept will consist of values, ratios, and patterns that represent preferred evolutions of the SoS.

D. Limitations of results

Undoubtedly, this study represents both an exploration of a new concept and the use of a new approach. Therefore, care must be taken during the process of interpreting results so that effects due to the new concept can be discerned separately from artifacts of the new modeling approach. Further, this type of approach will not specify answers that are normally sought from engineering concept studies for aircraft. Again, the emphasis of the former is finding high-level patterns over a range of possible future scenarios whereas the latter seeks a particular "answer" in the deterministic sense.

II. System of Systems Background

A. What is a System-of-Systems?

System-of-Systems problems consist of multiple, heterogeneous, distributed systems involved and embedded in networks at multiple levels that address national public needs. Attempts to categorically define the SoS problem are counterproductive, since it focuses on artifact (the name) as opposed to the challenge itself. The consideration of unique traits and behaviors are more valuable, and with these we can "know one if we see one". Further, the development of effective methods will depend on this understanding. An introductory description of the traits of an SoS problem is offered in Table 1. When a preponderance of these traits is observed, an SoS problem is at hand and thus characteristic behaviors can be expected.

Table 1: Description of Key SoS Traits

Traits	Descriptions
Operational Independence of Elements	Elements have their own unique purposes & can operate independently
Managerial Independence of Elements	Elements are provided unique purposes by their owners & operators
Evolutionary Development	SoS is constantly changing, never fully formed
Emergent Behavior	Properties of whole emerge from the assembly of elements
Geographical Distribution	Elements are physically distributed; linked by communication
Heterogeneity	Elements are different in nature; different dynamics & time scales
System of Networks	Networks define connectivity between elements through rules of interaction
Trans-Domain	Study requires unification of knowledge across many fields: engineering ∪ economy ∪ policy ∪ operations ∪…

Approaches for SoS problems are focused on the understanding of emergent behavior and evolutionary development. *Emergence is the discovery of patterns or properties at the upper levels of hierarchy of SoS problems that arises from interaction in lower-level systems operating in the midst of some connectivity – emergence cannot be observed by scrutinizing the constituents in isolation* or be precisely predicted ahead of time. The global behaviors that are observed with emergence do not necessarily follow intuitive thinking and thus, require careful scrutiny before being accepted. Further, emergence can be observed for positive and negative outcomes. This provides the capability to implement successful architectures with uncovered "jackpots," while also maximizing the situational awareness of vulnerabilities, the "landmines," in these architectures.

B. Why is SoS important for this application?

Lexicon is important because we need to translate the given problem into terms we understand unambiguously and ensure a complete description. Lexicon, or language, is the essential part of the needed framework to allow the new practitioners of this field to think, communicate, and design collaboratively as well as produce a useful product to the decision makers. A working lexicon has been crafted and is intended to reduce ambiguity and lead to effective mathematical modeling for System-of-Systems problems.[1] This "embryonic" lexicon framework consists of two major structures (shown in Figure 1): categories of systems and levels of hierarchy.

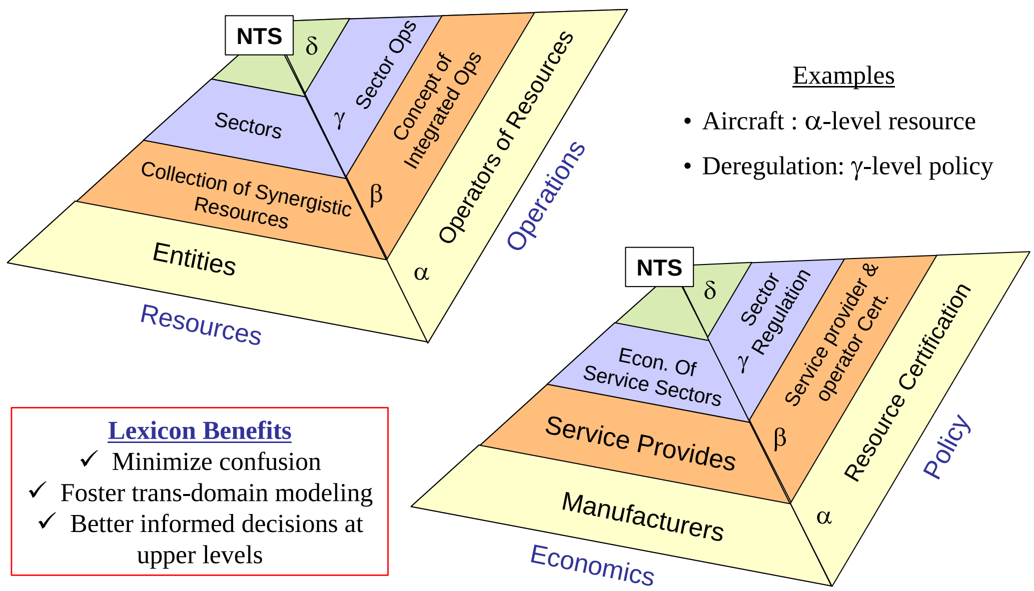


Figure 1: Lexicon for System-of-Systems Treatment of Transportation

The categories highlight one important distinguishing trait of System-of-Systems problems: the heterogeneous mix of engineered and sentient systems together in one problem setting. For each category, there is a hierarchy of components. To avoid confusion with ambiguous derivations (e.g. system $\rightarrow$ System-of-Systems $\rightarrow$ architecture), the lexicon employs the unambiguous use of Greek symbols to establish the hierarchy. This is a formalization of the use demonstrated in the last sub-section. Alpha (α), Beta (β), Gamma (γ), and Delta (δ) indicate the relative position within each category. The collection of α entities and their connectivity determines the construct of a β-level network and likewise, a γ-level network is an organized set of β networks. Hence, the δ-level can be described as a network with varying levels of α,β,γ networks and at each higher level the number of combinatorial possibilities increases.

C. Using the Lexicon in a transportation setting

The use of the lexicon introduced in Figure 1 is exemplified in Figure 2, illustrating how the NTS could be described in a SoS frame of reference. This use of the lexicon provides value at two levels: first, the breadth of the problem and subsequent imperative to move beyond (across) domain stovepipes is evident, and second, the categorizations help effectively guide the *later modeling activities*. The variety of decision-makers involved in transportation can be identified, engaged, and included in the discussion. Through subsequent modeling, the probabilities for solutions at the γ- or δ-levels can be formed by aggregating the α- and β-level entities. It is also important to note the number of entities at each level may vary tremendously, likely by orders of magnitude. For example, in Figure 2, estimates are given for the number of entities at each level, ranging from 10^6 to 10^2 in just two level shifts.

Level	Resources	Operations	Economics	Policy
α (ϑ 10^{7})	Vehicles & Infrastructure (e.g. aircraft, truck, runway)	Operating a Resource (Aircraft, truck, etc.)	Economics of building/operating/buying/selling /leasing a single resource	Policies relating to single resource use (e.g. type certification, flight procedures, etc.)
β (ϑ 10^{4})	Collection of resources for a common function (an airport, etc)	Operating resource networks for common function (e.g. airline)	Economics of operating/buying/selling /leasing resource networks	Policies relating to multiple vehicle use (e.g. airport traffic mangt, noise policies, etc.)
γ (ϑ 10^{2})	Resources in a Transport Sector (e.g. air transportation)	Operating collection of resource networks (e.g. ; commercial air Ops)	Economics of a Business sector (e.g. Airline Industry)	Policies relating to sectors using multiple vehicles. (safety, accessibility, etc.)
δ (ϑ 10^{1})	Multiple, interwoven sectors (resources for a national transportation system)	Operations of Multiple Business Sectors (i.e. Operators of total national transportation system)	Economics of total national transportation system (All Transportation Companies)	Policies relating national transportation policy
ε (ϑ 10^{0})	Global transportation system	Global Operations in the world transportation system	Global Economics of the world transportation system	Policies relating to the global transportation system

Figure 2: Mapping of Transportation SoS Elements using Lexicon

D. Bringing it all together: Transportation Abstraction

An abstraction for transportation that builds from the levels and categories has been carefully developed[2] and serves as the guide to building the system-of-system NAS concept for the RSCA project. A brief summary is given here to highlight the role of this phase in the SoS proto-method. Two pairs of entity descriptors emerge from the abstraction process: explicit-implicit and endogenous-exogenous. Unlike under the reductionism mindset, the role of the descriptors is not to facilitate break-down of the entities into separate pieces. Instead, it is only to organize them by articulating their inherent natures. Four entity categories are generated based on the descriptors: resources, stakeholders, drivers, and disruptors. All these entities are inter-webbed by networks that define the linkages amongst themselves. This is summarized in Figure 3.

Vehicles and infrastructure are examples of resources that consumers physically experience (explicit) when traveling or sending shipments. Further, they are under partial or full control of those who own and operate them, thus endogenous. But there are ‘other-than-physical’ entities that desire to exert forces on the architecture for their own interests. This type of endogenous entity is called stakeholder, and in most circumstances their behaviors and decisions are not manifested in an explicit manner to the consumers (implicit). The stakeholders reside in both private and public sectors, ranging from the actual consumers of transportation services to the providers of those services. Each stakeholder holds objectives they wish to pursue in the transportation environment. For example, an individual values doorstep-destination (D-D) speed, cost per mph, mobility flexibility, etc. However, from a societal perspective, there may be desires to minimize total energy expended, maximize the robustness of the system to disturbance, etc. Often, members of these two groups move in tandem (e.g. robustness of system and mobility freedom), but other times they may not (e.g. possible increase in energy per mile traveled in an on-demand system).

While the stakeholders and resources are considered endogenous building blocks, the transportation environment contains exogenous entities that are outside of the architect’s controllable domain. This entity class has been traditionally treated as given assumptions, circumstances, and constraints about the transportation environment (e.g., population, weather). Driver entities are largely concerned with

economic, societal, and psychological circumstances that influence the stakeholder network by implicit means. On the other hand, disruptor entities explicitly affect the resource network and/or a portion of the driver entities by reducing the efficiency of the resource network, disabling particular nodes or links of the network.

The transportation abstraction in Figure 3 identifies networks existing in both the resource and the stakeholder domains. For example, air transportation resource networks arise when nodes (airports) are linked by aircraft either in a scheduled or un-scheduled (on-demand) manner. The connectivity provided by the commercial airline industry is determined by pre-defined schedules and is presently by far the predominant means of air transportation. Charter, fractional ownership, and personally owned options exist, but they remain at least one order of magnitude higher in cost than the scheduled service. Demand, which theoretically drives schedules, is an important component of the real networks. Thus, in contrast to the present network, unscheduled (on-demand) models are also being increasingly studied. On-demand implies that the systems organize themselves to serve a particular demand of a particular customer at a particular time. In this case, ad-hoc networks would be formed to respond to demand, requiring a flexible set of vehicles and traffic management rules to do the job.

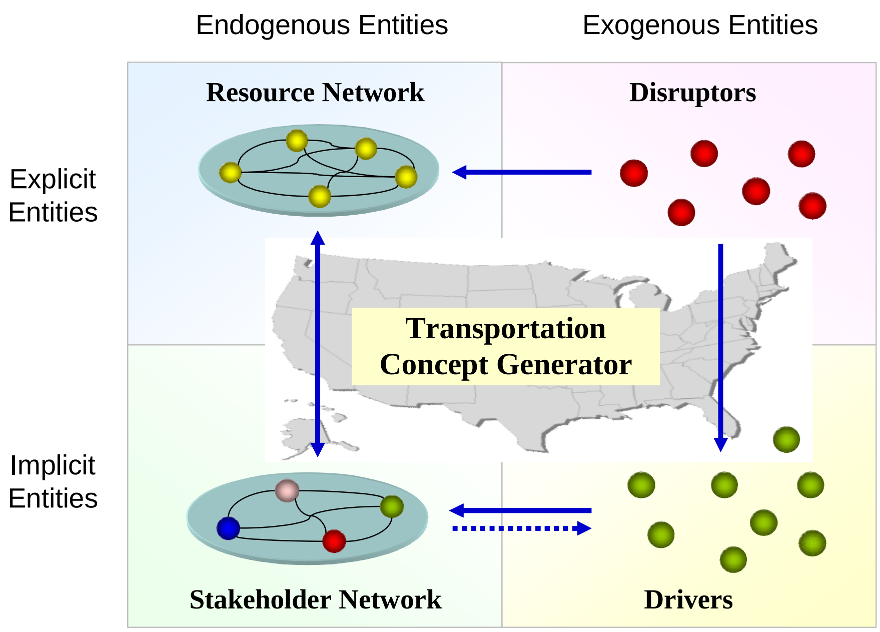


Figure 3: Transportation Abstraction Model

III. Analytical Approach

The analytical approach for this RSCA study rests on utilizing the System-of-Systems approach described in Section II in the context of finding concepts that point towards a desirable new NAS. In actuality, the scope of formulation extends beyond the NAS to include other modes of transportation. Instead of examining the NAS solely as the study of airports, air traffic, and personnel, the abstraction model of Figure 3 allows for consideration of the entire NTS. However, the time duration of the RSCA study did not allow for exploitation of this larger scope. Thus, while the results reported herein primarily constitute the air portion, the interfaces have been designed (and implemented in several instances) to later include the other modes in an explicit manner.

A very insightful encapsulation of these possible networks (shown in Figure 4) as well as the various layers within the resource networks has been presented by Holmes.[3] For example, the *capacity network* has its nodes as points of entry, or portals, into the transportation system and the links are some

mode of travel between nodes. This idea is presented in a general manner. The essential model behind our concept is that of network. In our initial research on the network topologies, we have focused primarily on the capacity network. However, as will be explained later, we have begun to investigate through simulation linkage between the mobility and capacity layers for the purpose of exploring the tight connection between these two networks.

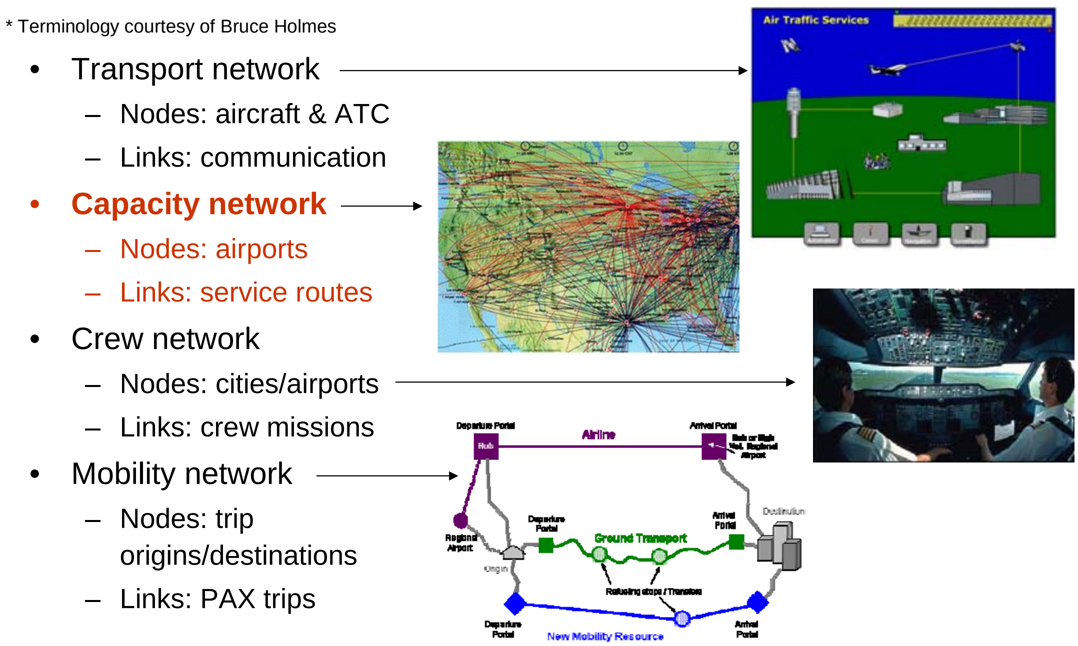


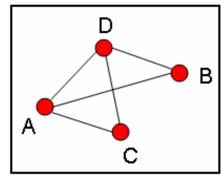
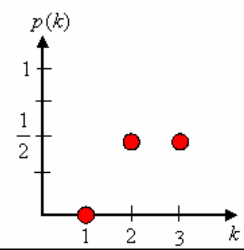
Figure 4: Networks in the NAS and their topology definition

We know from the transportation abstraction that any of these resource networks will evolve according to behaviors of stakeholders and under the influence of disruptors and drivers. Therefore, the heart of our technical approach to generating our RSCA concept is the combination of network modeling (via Network Theory) with agent-based modeling (ABM) within one simulation- essentially a "synthesis code" for air transportation systems. The ABM represents stakeholder behavior rules and these rules drive the evolution of the network. Concepts from Network Theory enable discernment of good, or bad, outcomes; over a collection of outcomes, then, patterns in the results can be sought. The next two sub-sections of this major section describe the important fundamentals of Network Theory and ABM as well as how they were applied in this study.

A. Modern Network Theory

A research premise is that we are no longer able to exclusively employ traditional engineering methodology-especially a bottom up approach- due to the high complexity of current and future air transportation system. We are also incapable of effectively predicting its response in which the constituents are not possibly well defined and governing laws are also not well understood. Hence, innovative and powerful analytical tools are needed to craft a simulation-based approach. The development of modern Network Theory sheds light on potentials in analysis of large scale systems. Our preliminary research focus was placed on the network dynamics which accounts for the formation of network topology while network topology is responsible for the capacity and vulnerability of networked systems. We look forward to finding out its application in analysis of scalability and robustness of air transportation system. The following is the terminology commonly used in Network Theory.

Table 2: Network Theory- Definition of Terms

Measure	**Description**	**Equation or Example Calculation**
Degree & Density of the network:	Degree : it is the number of links connected to a node; Density is the ratio of the number of the links (*m*) to the number of the nodes (*n*),	Density: 5/4 Degree of node A: 3 
Incidence matrix	Representation of the network topology in matrix form	$A_{ij} = \begin{array}{cc} \begin{matrix} A & B & C & D \end{matrix} & \\ \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} & \begin{matrix} A \\ B \\ C \\ D \end{matrix} \end{array}$
Degree Distribution	Degree distribution defines the probability of a randomly chosen node with *k* links; it can be utilized to observe network topology with high complexity	Ex. In the 4-node graph above, nodes B and C have two links and the other two nodes(A, D) have three links which bring about the following degree distribution 
Clustering Coefficient	A measure to quantify the cliquishness of a given network; that is one way to measure how close the constituents of the network are, which has implication for the robustness of the network.	$C_i = \frac{number\ of\ triangles\ connected\ to\ node\ i}{number\ of\ triples\ centered\ on\ node\ i}$ Ex. In the graph above, $C_A = C_D = \frac{2}{3},\ C_B = C_C = 1,$ $\Rightarrow C_{Average} = \frac{5}{6}$
Average Shortest Path	The average values of shortest distance between each pair of nodes in a given network. $l = \frac{1}{\frac{1}{2}n(n+1)} \sum_{i \geq j} d_{ij}$	Ex.: In the graph above, the average shortest path can be calculated as follow: $d_{ij} = \begin{array}{cc} \begin{matrix} A & B & C & D \end{matrix} & \\ \begin{bmatrix} 0 & 1 & 1 & 1 \\ 1 & 0 & 2 & 1 \\ 1 & 2 & 0 & 1 \\ 1 & 1 & 1 & 0 \end{bmatrix} & \begin{matrix} A \\ B \\ C \\ D \end{matrix} \end{array}$ Average shortest path: $l = \frac{7}{10}$

B. Validation of Modeling Approach on present US air transportation capacity network

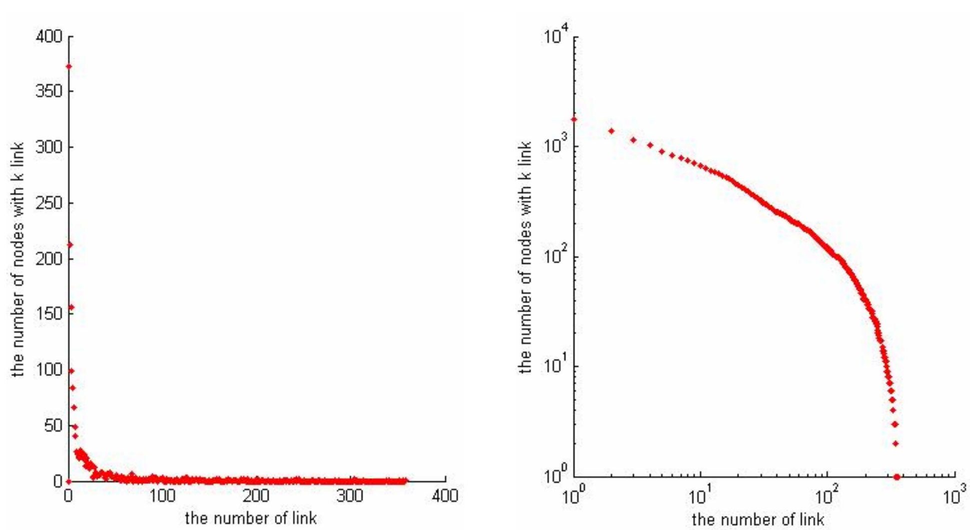
The data source for our empirical studies is the U.S. Bureau of Transportation Statistics (BTS).[4] The BTS data service is free and the database is available online (for commercial air data after 1990). Users can establish a set of sort criteria and the requested dataset is generated. The BTS database contains both passenger and flight operations data over a one month and one year window (one month is the smallest time period reported).

We have developed MATLAB code that can analyze a given topology through calculation of its cluster coefficient, average shortest path, density, etc. as well as plotting of the degree and cumulative degree distributions as seen below. As a side note, we have also begun to investigate available freeware tools for network analysis. One of the most well-known is *Pajek* (pronounced "pie-yak"), the Program for Analysis and Visualization of Large Networks.[5] While it has been extremely valuable for us to create our own analysis tools from a pedagogical perspective, we hope that more sophisticated software can overcome some computational inefficiencies.

Even with the accessible data from BTS, empirical studies of air transport networks are not straightforward because of a very basic issue: *What is a link*? Though we will revisit this question in more depth later on, even an initial attempt to analyze a simple transportation network topology requires careful answer of this question. In our studies, we have explored the definition of link in terms of number of passengers, number of operations, and number of cities served, respectively. Use of passengers for link definition is attractive since we are interested in personal mobility studies, so the exclusion of cargo flights seems acceptable. However, cargo flights are part of the load on the network. Fortunately, the point is, on average, moot since we determined that the number of cargo flights annually is insignificant compared to passenger flights.

In particular, we compared two types initially in order to make an initial representation of the current air transportation network (commercial service): a) number of departure *operations* at all airports with US originating/arriving commercial flights and b) number of US *cities served directly* from each US airport. We found that the number of cities served directly is an acceptable surrogate measure for number of operations, i.e. the degree rankings in each case are fairly close aligned.

Our first set of validation results is for consideration of undirected, un-weighted commercial capacity network where a *link is defined as there being one or more passengers traveling between nodes per year*. Results for the empirical analysis of the 2004 U.S. commercial air network appear in Figure 5.



a) b)

Figure 5: Empirical analysis for 2004 U.S. commercial air transportation network: a) Degree distribution in linear-linear scale and b) Cumulative Distribution in log-log scale

We now carefully interpret the empirical results obtained. First, a general rule for determining the existence of scale free behavior "by inspection" is that there must be linear behavior for at least **2 decades** on each axis of a log-log plot of the cumulative distribution that exhibits the sufficiently complex network structure (well-developed networked systems). Inspection of Fig. 5b) shows the requisite two decades of linear behavior (power law relationship) but followed by "*decay*" in the tail at high values of degree. Amaral and others attribute this sharp cutoff to limits on addition of new nodes (nodal capacity limits).[6] While a pure scale-free model predicts more links for the hubs in the air transportation network than are observed, we can understand the truncation tail by the capacity constraints present in our "real world hubs".

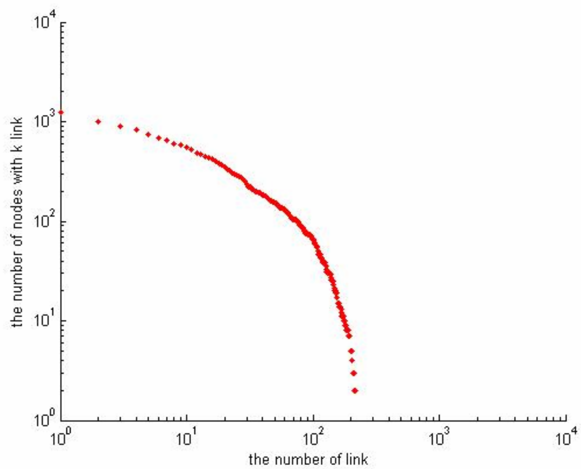
Finally, we examine the question of link definition in a very specific way by looking at two different link definition schemes for the 2004 data. Network "A" using the flights-based definition while Network "B" using a passenger based definition. The results are given in Table 3 and Figure 6. The key metrics of *C* and *l* as well as the cumulative probabilities indicate that these two paradigms give essentially the same "performance" though there are structural differences in representation. The run-time was significantly higher than expected, and we pinpointed the problem to the average shortest path calculation. We further determined that it is the sparseness of the incidence matrix that is the culprit. Our definition of sparseness is illustrated in Table 4. We tested our assertion that sparseness is the primary driver by setting a lower probability in a randomly-generated incidence matrix that creates a sparser matrix. The runtime exhibited significant increase in the case of sparse-matrix.

Table 3: 2004 Network Definition Comparisons

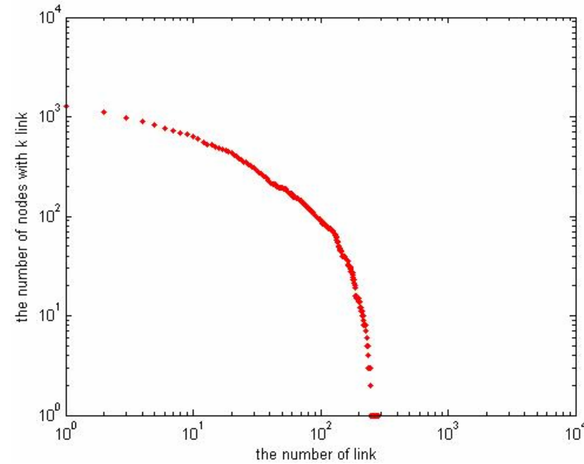
Metric	(A) Link Definition: Link exists if at least 2 flights per year between nodes	(B) Link Definition: Link exists if at least 50 PAX/year between nodes
Average Clustering Coefficient *(C)*:	**0.57474**	**0.56434**
Average shortest path *(l)*:	**3.5495**	**3.0735**
Average Degree *(<k>)*:	12.094	26.437
Network complexity:	6.0468	13.218
Network size *(N)*:	1036	1259
Total number of degree *(m)*:	12529	16642
Maximal Degree:	173	285
The number of clusters:	32	2
The size of the largest cluster:	992	1257
Run time:	19823(sec) (5.5 hours)	

Table 4: Sparseness calculation for incidence matrix

Total number of non-zero elements in *A*:	12529 (6238, 6207, 84)
Total possible links:	536130 (1036*1035/2)
The actual links:	7195 (directed network)
The ratio of sparseness:	12529/1073296=0.0117



Network A: Link if ≥ 2 flights per year



Network B: Link if ≥ 50 passengers per year

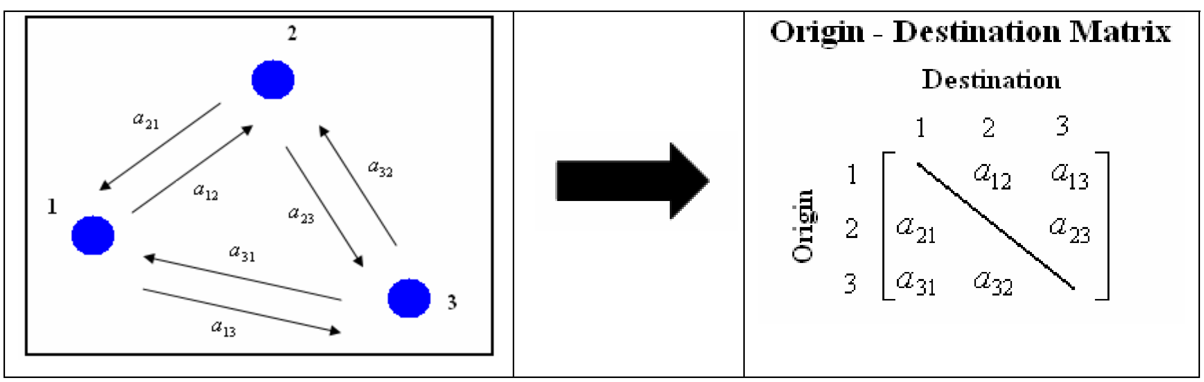
Figure 6: Comparative Cumulative Distribution plots for Networks "A" and "B"

C. <u>Mapping of Network Theory to NTS Measures</u>

In order to be of practical use, these mathematic characterizations of networks must be translated, or mapped, into the metrics that are germane to the NAS- *capacity/throughput*, *delay*, and *robustness*. Three metrics tend to dominate discussion of measures of goodness for the system: throughput (or capacity), delay, and robustness. These are actually interrelated!

<u>Throughput / Capacity</u>

Throughput measures the number of operations processed by an airport within a given time frame (e.g. the number of flights per year either in arrival, departure or the sum of both). Capacity represents the upper limit on throughput. In Network Theory, we can quite easily assign a capacity to a particular node; however, determining capacity of an actual airport is difficult. Our investigations have found that many (often unquantifiable) factors determine capacity on a given node. In our case, the throughput of a particular node can be calculated using a weighted and directed flight origin-destination (OD) incidence matrix, such as the one shown below.



Therefore, the number of departure, arrival and the total operational flights *(throughput)* of an airport can be determined by calculating the equations below:

$$\sum row_i + \sum col_i = \text{Total operations per year for node i}$$
$$\sum row_i = \text{\# of departures per year for node i}$$
$$\sum col_i = \text{\# of arrivals per year for node i}$$

Delay

Delay is usually calculated through traditional network analysis and queuing models, and even then notoriously difficult to compute accurately at each individual airport. In this study, this type of analysis and its complications are avoided by exploiting an innovative use of our topological network tools to capture the essence and root cause of delay. Thus, the conventional description of delay as in ‘waiting time’ for a particular node (airport) will not be calculated. Instead, relative probability for delay at node(i) can be described through a ratio between total demand (as measured by the average degree of those neighboring nodes connected to node(i) and maximum throughput capacity of the node (airport).

$$Delay(i) = func(capacity_i, demand_i) = f(k_i, \langle k \rangle_{neigh}) \tag{1}$$

Our initial examination of actual delay data shows that the degree of a node and actual delay is positively correlated; since usually it is more likely for an airport that is operating at a higher utilization rate to experience delays than those that are not.

Most of the data were tabulated in functional forms that support the Network Theory approach, such as: number of links, number of operations, etc. for each node so that the data can be easily implemented in the simulation.

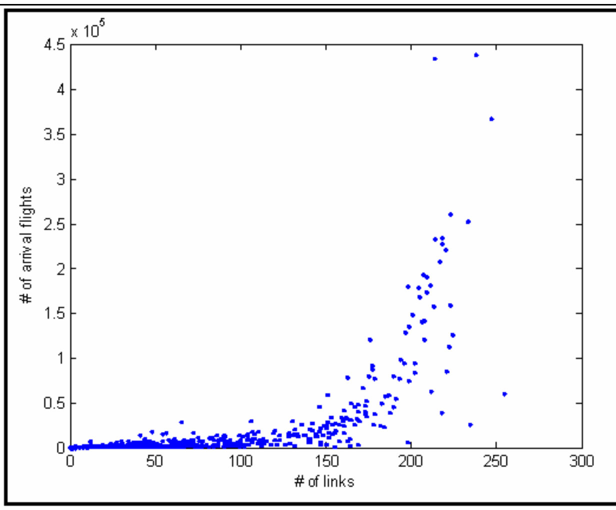


Figure 7: Number of Arrival vs. Number of Links for Domestic Airports (2004)

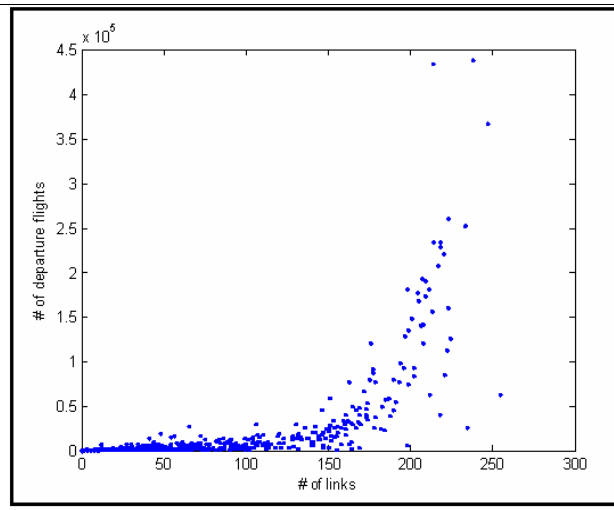


Figure 8: Number of Departures vs. Number of Links for Domestic Airports (2004)

One example data set that is created in such a form is displayed in Figure 7 and Figure 8, which shows the number of arrival and departure flights an airport annually experiences as a function of their number of links. The question of how to define a link in the context of this work was a very difficult one (and remains so). The current data reported defines a link as the presence of a route between two airports that occurs at least twice annually. Trends in the two figures clearly exemplify today’s hub-and-spoke network topology. Airports with more than approximately 150 links display a marked increase in the ratio of flights to links and thus can be considered as hub airports. Some of those hubs are well known

'congested' airports such as ORD, LAX and ATL. Traffic statistics for the top 5 busiest airports are reported in Table 5. Within the simulation, air traffic for the airports can be approximated using the number of links and the empirical relations shown in Figure 7 and Figure 8.

Table 5: Traffic Data for Top 5 Busiest Airports (2004)

Airport	Departures	Arrivals	# of Links
ATL	437,729	437,176	238
ORD	433,785	433,158	214
DFW	366,532	365,833	247
DEN	259,824	259,732	223
LAX	251,354	251,617	233

Another important set of data collected was the correlation between delay and number of links for an airport, in which a flight was considered "delayed" by the BTS (as well as the FAA) when the operation was completed 15 minutes or more behind schedule. The results of this correlation can be seen in Figure 9. The relationship between delay and number of links were surprisingly well represented by a curve with an R^2 value of 0.92 when expressed as a 2nd degree polynomial. Based on this observation, delay and network saturation of the simulated NAS were computed. However, converting these delays into the standard "wait-time" (minutes) for a more detailed NAS investigation requires further study and analysis.

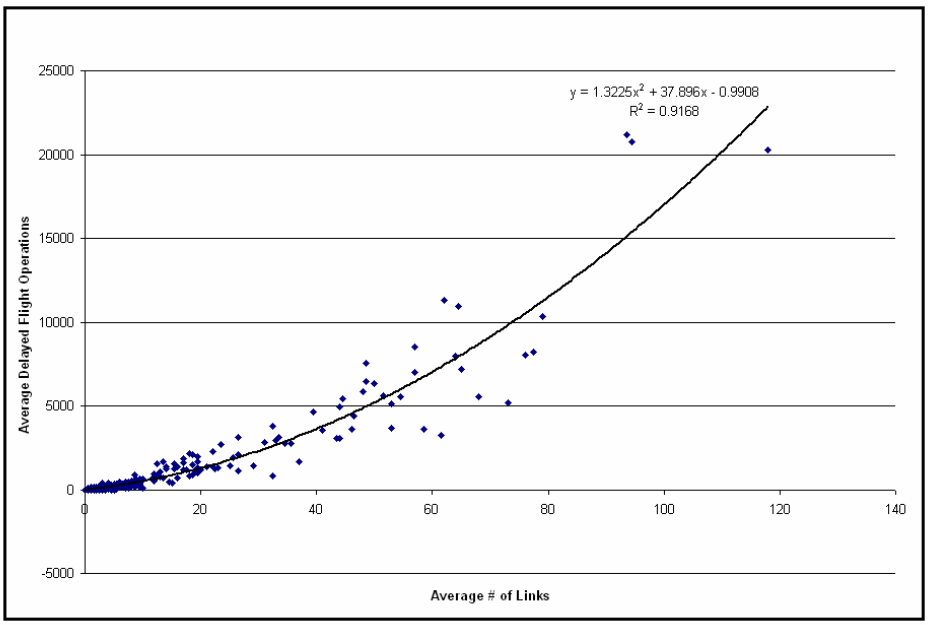


Figure 9: Average Airport Delay Ops vs. # of Links for Feb & Nov. 1990

Robustness

One cannot speak generally about robustness; instead, a particular disturbance or class of possible disturbances must be specified in order to measure or estimate a particular robustness. We see four types of interest, meaning we are interested in whether a system is robust to the following:

- Complete nodal failure
- Nodal degradation
- Implementing new technology
- Demand scaling and shaping

There are two general types of “attack” that may cause complete nodal failure: targeted and random. These attacks disable the function of a node (airport) and either temporarily or permanently removes it from the entire network. Random attacks are arbitrary failures that can occur to any nodes within the network. They usually represent incidents such as weather, accidents and aircraft malfunctions within the NTS. Targeted attacks, on the other hand, are failure of specified nodes usually due to an artificial cause. In the real world, targeted attacks may occur as terrorism, strike or war-related issues. Since these are targeted, we often refer to the lack of robustness to these as “vulnerability”.

In this context, the mapping of measures from Network Theory to actual NAS network robustness and vulnerability to such attacks can be measured as a function of the *clustering coefficient* before and after the node failure. By calculating degrade of the clustering coefficient after an attack, the immunity of a network to different type of attacks can be practically be determined.

$$Robustness = func(C_{i\_after\_attacl}, C_{i\_before\_the\_attack}) \qquad (2)$$

The literature has shown that scale-free networks are robust to random failure but vulnerable to targeted attack. Robustness to demand scaling and shaping will be addressed in our RSCA concept results presented in Section V.

All three of the “mappings” from Network Theory measures to NAS performance measures are collected in a concise manner as shown in Figure 10.

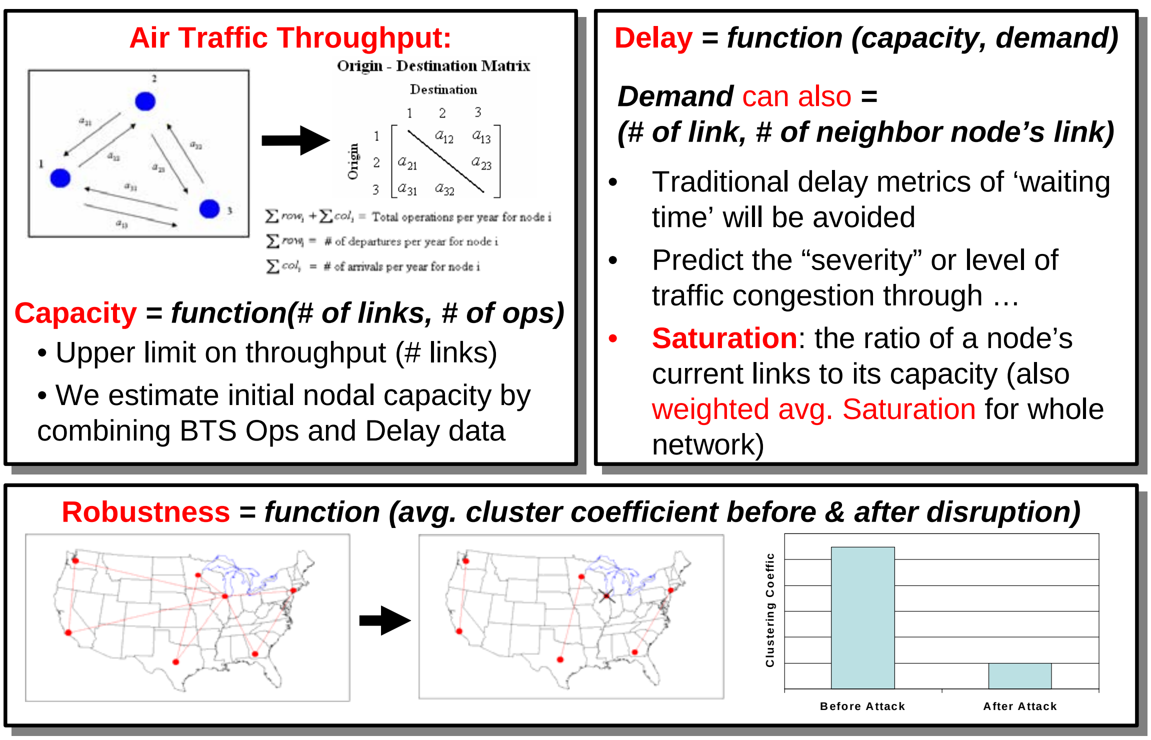


Figure 10: Summary of Mapping of Network Theory Measures to NAS Performance Metrics

D. Agent-based Modeling (ABM)

Agent Based Modeling (ABM) is a system that is modeled as a collection of distinct decision making entities called “agents”. Traditionally, scientific analysis has been done either by induction, where patterns are observed over a specific data set or by deduction which existing theorems are used to explain

certain phenomena. However, ABM uses another method of approach: simply model a collection of dynamic systems with a minimal set of interaction rules and observe what happens. The ultimate goal of ABM is not to prove, but to understand processes that are not obvious from data or proofs about a complex, non-linear system. ABM will be used to simulate interactions between the individual entities (agents) within the NAS. Since ABM can capture the interaction between independent stakeholders and thus produce emergent phenomena, it is an important ingredient in the study of System-of-Systems. In the particular case of this RSCA study, ABM can teach us something about the evolutionary mechanisms specific to air transport system.

E. Why use agent modeling in this study?

In the previous section it was establish that particular networks exist in the larger NASA construct and that we can analyze these networks effectively using Network Theory. But how do these networks actually arise in air transportation? How do they evolve? How are they reshaped by external events and particular actions of stakeholders? In the development of modern Network Theory, several possible evolutionary mechanisms and constraints to account for the development of the network topology have been proposed. However, such networks can only arise if there is an economic imperative to do so. Thus, the use of agents to mimic the real world—where the stakeholders identified in the abstraction model of Figure 3 interact with each other and the environment based upon self-interest—becomes a logical step in the simulation.

F. Implementation of Multi-Agent Simulation (MAS)

The employment of multi-agent simulation (MAS), an ABM in which a variety of agent types exist, can be characterized by four constructs:

- Agents- the simulated behavioral entities (of various types)
- Objects- set of all passive entities (e.g. airports, enroute space)
- Environment- topological space where agents and objects are located
- Communications- set of all possible communications between entities

Additionally, there are a variety of types of agents. *Spatial* agents are those in which movement through a geographic space is important. *Reactive* agents are those who simply act based an execution of a fixed set of rules. *Adaptive/Intelligent* agents, on the other hand, can modify their rules (and underlying beliefs) based on feedback from the environment after their previous actions. Typical agent logic is described in Figure 11.

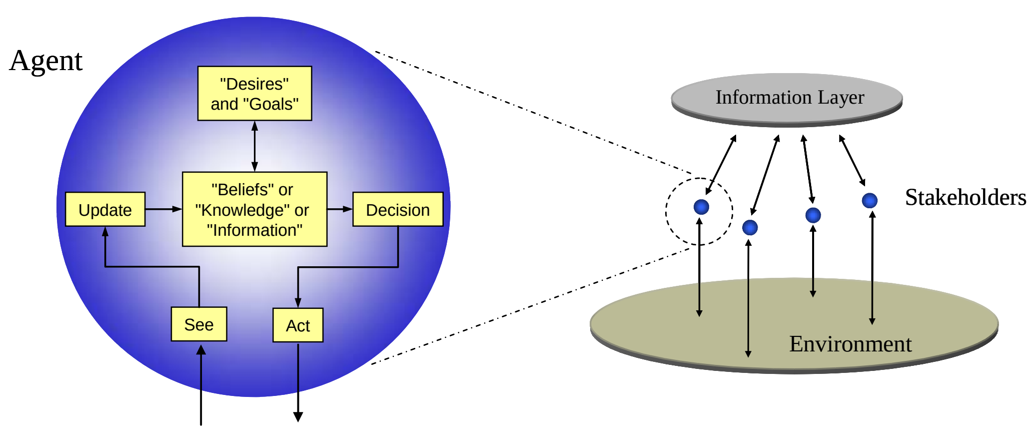


Figure 11: Generic Agent Construct

In building our agent-based simulation, we will follow the "goals of good agent-based programming" put forth by Axelrod[1]:

- Validity- the program correctly implements the model
- Usability- user can run program, interpret output, and understand how it works
- Extendibility- program can be adapted for future (related) uses

G. Agent types and basic functions

The evolution of the NAS network is directed by stakeholder agents that make choices based on simple rules on their perception of environment. Broadly speaking, these choices include the advancement of alternate modes of intercity travel (e.g. ground modes) and by reconfiguring the capacity network (e.g spreading the demand in the air capacity layer more evenly via a point-to-point travel instead of hubbing). In the particular scope of the RSCA study, two stakeholders (agent classes) were emphasized: service providers and infrastructure providers. Description of these two agent types are given in Table 6.

Table 6: Primary Agent Types in the Simulation

Agent Type	*Real Stakeholder Examples*	*Goals Actions (variable names in **bold**)*
Service Provider		Main Goal • Meet as much of Demand as possible within niche Two SP Agent Types: • *Long-Dist* and *Regional* Actions • Query nodes, act when distance (**SP1**) & demand (**SP2**) thresholds met • Add link with some probability (**SP3**)
Infrastructure Provider		Main Goals • Maintain adequate capacity • Reduce delays Actions • Query nodes, detect capacity need • If needed, add capacity increment (**IP1**) with some probability (**IP3**) • Time to implement add (**IP2**)

IV. Analysis Integration

A. Model for Integrated Simulation

Fundamentally, our model is not a trip-based model (e.g. the transport network). Instead, we are looking at a capacity network model that is, however, influenced by what happens in the mobility network (relative levels of demand between regions). The demand will likely change by shifts in percentages of people who want to go from one region type to another (this is demographic effect). The mechanisms that make up the implemented simulation architecture are shown in Figure 12.

[1] Axelrod, R., *The Complexity of Cooperation*, Princeton University Press, Princeton, NJ, 1997.

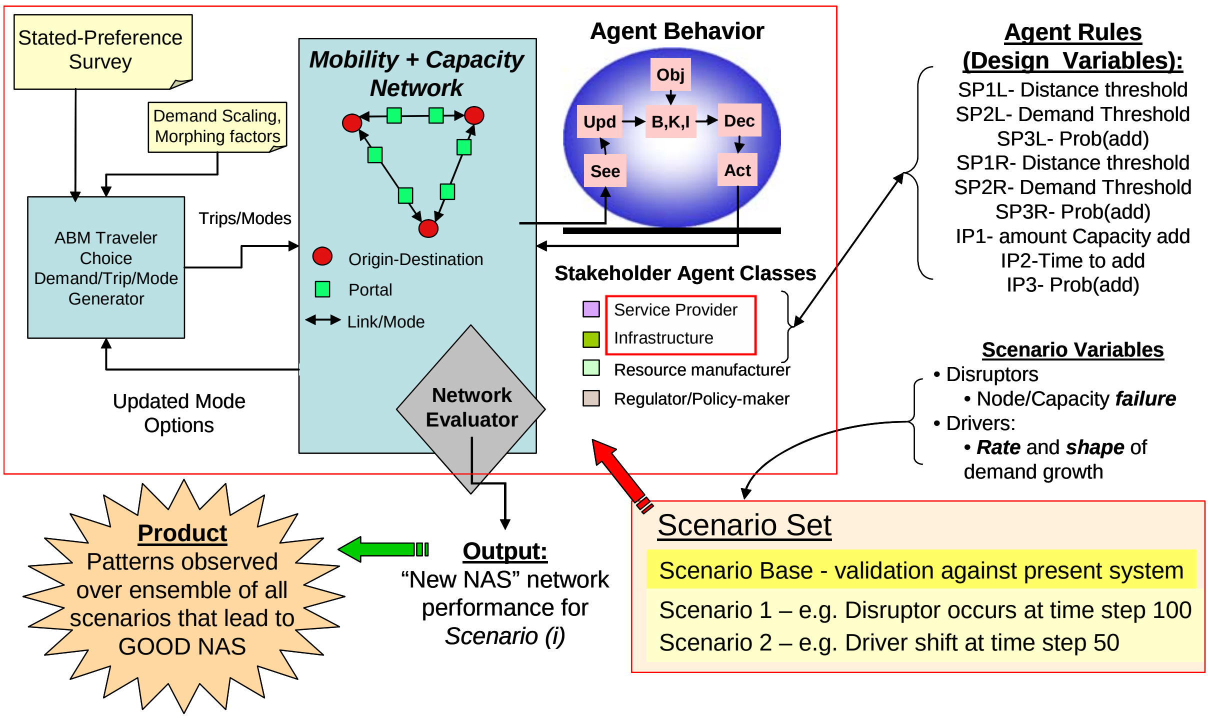


Figure 12: Simulation Logic Model

The overall scheme is simple: stakeholder agents (e.g. service providers, infrastructure providers, regulators) act to evolve a network under various scenarios (see Figure 1). Each agent is provided with a set of objectives and behaviors which guide decisions and then actions. Subsequently, the agent sees consequences from the environment and updates behaviors. The network analysis model plays a central role; it accepts both the measure of demand as well as the actions of agents in response to demand by allowing them to shape the network topology. Thus, a family of new topologies for the future can be evolved. The key question is: Do they exhibit good network performance both in terms of capacity and robustness? To address this question, a network evaluator is employed to compare the evolved networks to topologies that do exhibit preferred behaviors. Results of comparative topology studies will be tracked to understand which patterns in topologies and agent behavior lead to scalability. Such findings can be used to guide technology and infrastructure investments for future air transportation systems.

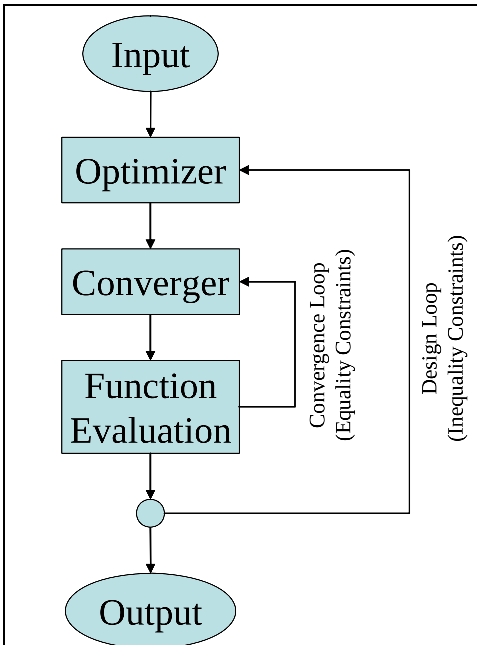


Figure 13: Generic Optimization Scheme

The traveler mode choice was not connected to the rest of the simulation architecture in the final analysis, though much of the background work to do this has been accomplished. A late start to this portion of the effort was an unforeseen complication in getting this loop closed.

B. The Role of Optimization:

Underlying the seemingly complicated information flows in Figure 12 is the simple desire to find the best settings for things that can be controlled, i.e. optimization. As stated early on in this report's motivation section, in an

evolving system-of-systems the key is to find the best rule set and network structure to allow natural behavior to produce acceptable global results. An optimization process is depicted in Figure 13 that could be executed using the analysis developed for this RSCA study. An optimization framework has several key parts: an objective function (or set of objective functions), equality constraints, inequality and decision (or design) variables. The Converger is similar to "sizing" strategy in which the iteration seeks to satisfy equality constraints. Often, convergence algorithms must be tailored for a specific application. The Optimizer is an "outer loop" iteration in which the goal is to determine settings of the design variables which optimize the objective while satisfying inequality constraints. Both the convergence and optimization loop rely on output of the function evaluator. Function evaluation is a potentially complex analysis, but is restricted to a single output, given a single input.

Though not fully completed in this short one-year study, the intent is to embed the simulation model represented in Figure 12 as the function evaluation box within an optimization process akin to that in Figure 13. By doings so, the overall objectives outlined earlier can be more rigorously pursued: the identification of minimal rule set (i.e. agent rule sets) and patterns in network structure that are most likely to lead to scalable results for the transportation metrics of import like throughput, delay, and robustness.

V. Simulation Environment

A. Primary Simulation Constituents

Already under development when the RSCA commenced, our N.T.S.S. (National Transportation System Simulator) was significantly enhanced over the term of this project. The simulator implements the analysis model that is explained in Figure 12. It compiles data imported from various resources and allows users to monitor the growing network attained and developed by variable agent based logic. The simulator allows users to record and save results using various network evaluation calculations.

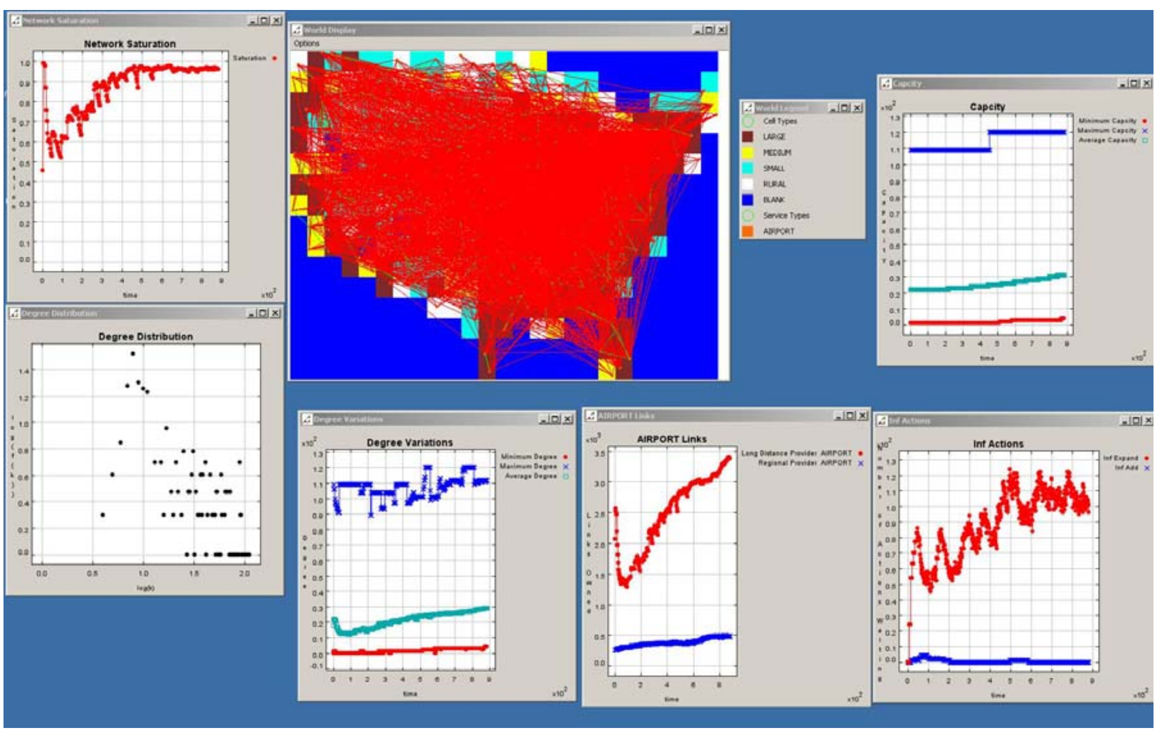


Figure 14: N.T.S.S Screenshot illustrating map view and network status graphs

The NTSS is based on the agent based modeling principal whereby agents of the system interact with each other in a simulated physical environment. This environment is often called “the world”. Characteristics of agents and the environment both can play important roles in the evolution of a System-of-Systems. Major elements of the environment are cells, nodes, and links. These are labeled in a snapshot of the “World View” shown in Figure 15 and are described next.

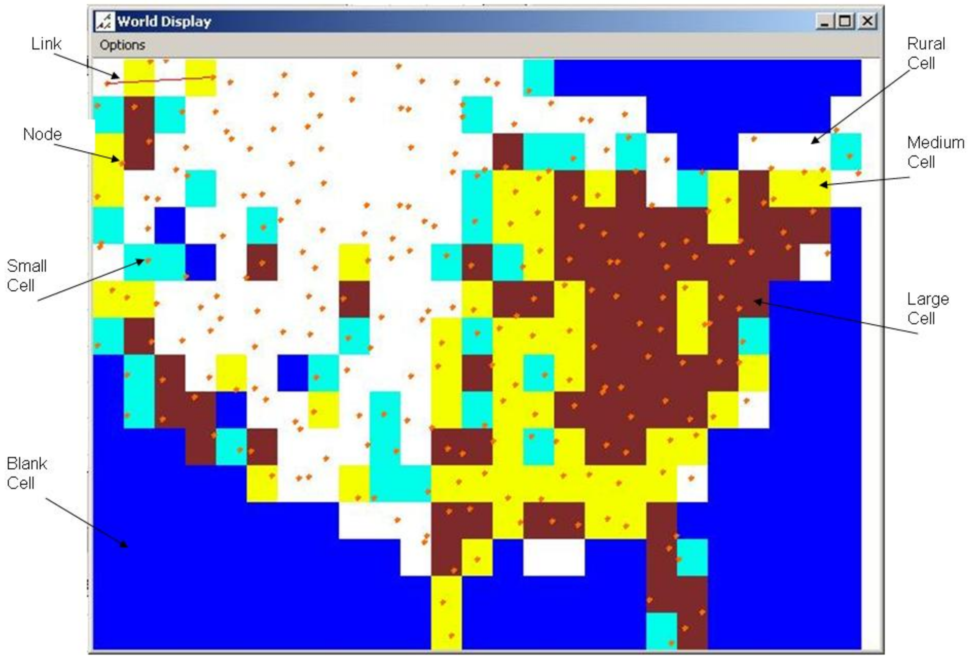


Figure 15: Screenshot of NTSS "World View" with explanatory notes

The world contains *cells* which are geographic regions with population and transportation demand values. Cell types, indicated by color in the world view, are based on their population level. These designators were used following the work of Lewe[7], who generally followed designation terminology of the U.S. Census data.

Table 7: World Cell Types and Descriptions

Cell Type	Color in NTSS	Description
Blank Cell	Blue	Non-influential geographic region usually symbolic of water.
Rural Cell	White	Symbolic of relatively small population and demand values.
Small Cell	Cyan	Symbolic of a small metropolitan area
Medium Cell	Yellow	Symbolic of a medium sized metropolitan area.
Large Cell	Brown	Symbolic of a major metropolitan area

Within cells of the world are *transportation nodes* which can represent a source of any mode of transportation (e.g. airport, train depot, bus station). For this RSCA study, nodes represented airports only as the complexities associated with including (explicitly) the other modes was beyond the scope of the

one-year study period. The essential data types associated with nodes are its location in a cell of the world, its capacity in terms of number of links, its actual number of links, and its service type, as listed in Table 8. The transportation links comprise the third major element type in the world. They represent a direct connection between nodes (though not necessarily the path taken between the nodes).

Table 8: Transportation Node Data Types

Data Type	Description
Geographic Location	The location of a node in the world (i.e. x, y coordinates)
Capacity	The maximum number of links supported by this node.
Transportation Links	Links attached to this node
Type	The transportation type supported by this node

In the prior section, especially in Figure 12, we identified the primary agents in our model: *Service Providers* (long distance and regional) and *Infrastructure Providers*. The tables below summarize the algorithms that were implemented to mimic the rules for these agents in the simulation. First, the Service Provider (SP) Agents act based on predetermined logic that determines whether and how they build or delete links between nodes in the system. The major parameters involved are listed in Table 9.

Table 9: Service Provider (SP) Agent Rule Parameters

Parameter	Description	Baseline Settings
Add Probability	Probability to add a link between two nodes after logic screening	Long Dist. **SP3L** = 0.2 Regional **SP3R** = 0.8
Delete Probability	Probability to delete a link between two nodes after logic screening	Long Dist. **SP3L-D** = 0.2 Regional **SP3R-D** = 0.5
Add Threshold	Minimum demand necessary between two nodes for link construction	Long Dist. **SP2L** = 40 Regional **SP2R** = 20
Delete Threshold	Maximum demand level necessary between two nodes for deletion of currently existing link	Long Dist **SP2L-D** = 30 Regional **SP2R-D** = 15
Minimum Length Threshold	The minimum length of a link for this Provider	Long Dist. **SP1L** = 50 pixels (200 miles) Regional **SP1R** = 0 pixels (0 miles)
Maximum Length Threshold	The maximum length of a link for this Provider	Long Dist. **SP1L** → None Regional **SP1R** = 60 pixels (240 miles)
Type	Transportation type associated with this agent	Air carrier

The Infrastructure Agents (IP) seeks to maintain adequate capacity of nodes in the system and, in rare cases, create new nodes. The logic of operation for the IP agents is based upon the following set of parameters.

Table 10: Infrastructure Provider (IP) Agent Rule Parameters

Parameter	Description	Baseline Settings
Add Probability	Probability to add a node after logic screening	**IP3** = 0.95
Delete Probability	Probability to delete a node after logic screening	0.0
Threshold	Minimum demand necessary to create or increase the capacity of a node	100 units
Average Time to Implement	Average Time needed to complete an action	**IP2** = 45 time steps
Percent Change	Change in capacity	**IP1** = 0.1
Type	Transportation type associated with this agent	Air

B. Overview of NTSS Run-time Activities

There are two stages that encapsulate the general flow of activities in the NTSS: Network Initialization and Network Evolution.

Network Initialization

The initial network can be either created at random or imported from existing data from the BTS (as described in Section 3.4). For this RSCA study, since we are interested in transformation of today's system, we wanted to start with today's lineage to the extent possible. Therefore, the NTSS is initialized using BTS data from the 1990 U.S. air transportation system overlaid on a 16x25 cell world. The 16x25 system was used due to the geographical state of the continental United States. The system is built with information regarding cell type based on U.S. census data, origin destination matrices and node initial capacities based on BTS data, and finally cell demands based on the aforementioned traveler choice model of Lewe.[7]

Network Evolution

The network evolves based upon the actions (and reactions) of the SP and IP agents. The ongoing feedback amongst the agents in the world environment gives rise to emergent behavior in the overall System-of-Systems network. At a more mechanistic level, the simulation proceeds through sequential execution of world actions, followed by IP actions, and then SP actions. At the end of this sequence, cell population updates are made by choosing a new population according to a uniform distribution that ranges between 98%-105%. At this point, the activities for the current time step are then complete. In order to have some relationship between "simulation time" and "real world" time, we carefully selected the baseline action time intervals for each agent or environment change. *Roughly speaking, one time step in simulation time is equal to one week "real" world time.* The individual agent time intervals are as follows: IP interval every 7 time steps, SP interval every three time steps, and cell action interval (population change) every 15 time steps.

Table 11: SP and IP Agent Rule Logic

Service Provider (SP) Agent	Infrastructure Provider (IP) Agent
1. Find node-pairs in world that have relatively high demand → forms set (H).	1. Find world cells where demand is high enough to require more nodes
2. CHECK: In set "not(H)", if a link exists in which demand is below demand threshold, delete this link with probability **SP2L-D** or **SP2R-D**	2. Add new node with probability **IP3**
3. CHECK: In set (H), is distance between nodes within length threshold for this SP. If YES, continue to 4)	3. If node to be added, schedule node addition
4. ACT: If no link exist, add link with probability **SP2L or SP2R**	4. If node exists, schedule capacity expansion

VI. RSCA Study Simulation Results

A. Review of Objectives

The ultimate objective in developing the concepts is to seek rules and patterns that lead to a "robust, scalable" transportation concept. We define Scalable as follows: the system is scalable if the system performance does not degrade with increasing, shifting demand. This means more than just the point solution of achieving a "3X" increase with the same general demand distribution. Further, thanks to the Network Theory formulation and NTSS, we can define and track system performance in terms of Throughput (the average degree in network), Delay (average nodal saturation), and Robustness (via the Avg. clustering coefficient).

B. Scenarios

The possible design variables include all of those listed on the right hand side of Figure 12. Recalling the specific manner in which the analysis then proceeds, we seek to run the simulation with different settings of the design parameters over several scenarios and then observe patterns in the results. In the context of this limited time study, three basic Scenarios are employed and are presented in Table 12.

Table 12: Scenario Descriptions

Scenario	Description
Scenario 1 (baseline)	Baseline demand growth (the population in each cell, and thus demand, grows according to a uniform probability distribution); **No Disruptions or Drivers are implemented.**
Scenario 2	Baseline demand growth; **Disruptor** occurs at time step 100; Five largest nodes are disabled
Scenario 3	**Driver** develops beginning at time step 50; STRUCTURE of demand changes dramatically, with significant urban-urban demand shifting towards more small-medium regions; Mimics demographic shift to more dispersed style of life, distributed transportation.

C. Revolutionary Concept I- Tunable Infrastructure Management

The first revolutionary concept is a flexible, agile, timely capacity management capability. This concept is discovered by examining two key parameters: the Capacity added by IP agent (multiplier of current node capacity), (**IP1**), and the Time to implement by IP (in ~weeks), (**IP2**). The specific objectives are the delay and robustness surrogate metrics, average node saturation and average clustering coefficient respectively. “Lower is good” for the saturation measure while “Higher is good” for the robustness. The results that display the patterns in behavior of the IP under Scenario 1 are illustrated Figure 16.

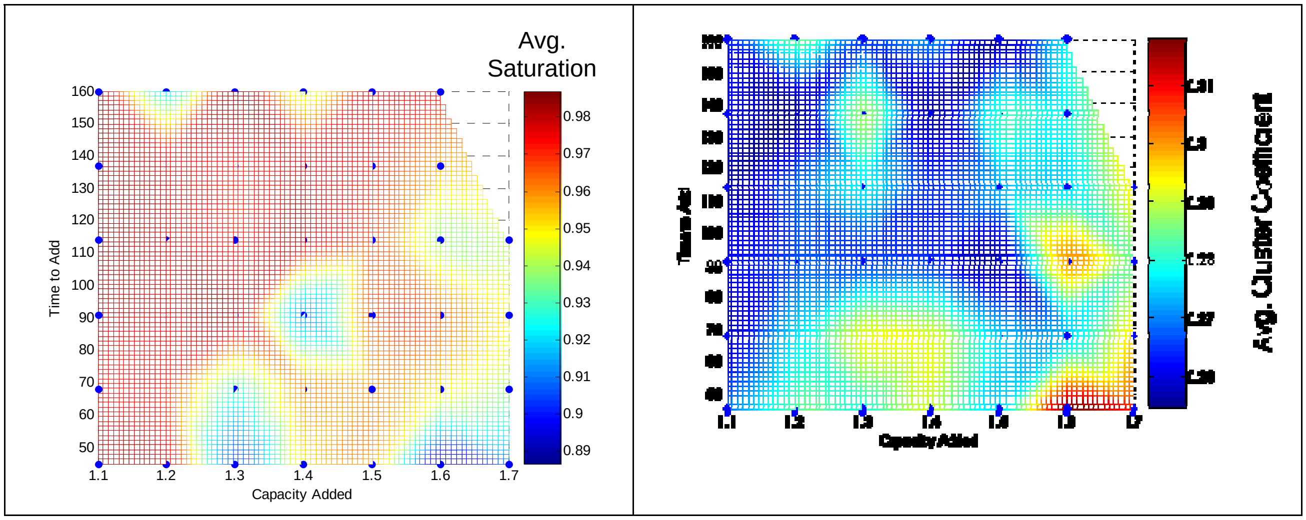


Figure 16: Simulation results for tunable capacity management concept

Interpretation of Concept Results:

- The combination of healthy additions of capacity (high **IP1**) in a rapid manner (low **IP2**) is required to moderate network saturation and minimize delay. There also seems to be a benefit to a particular ratio of (**IP1**/**IP2**). The primary implication is that we need an extremely flexible capacity network.
- The IP must add/move capacity quickly, inside the action time of SP business decision loops
    - “how quick” is just as important as “how much”.
- The impact of the ratio (capacity add) / (time to add) can now be quantified so that we can act for best connectivity. Further, actions can be identified that lie beyond the purely technological. For example, re-inventing the airport / airspace expansion process so that this nimbleness can be actualized would be an extremely important area of progress.

Logical Next Steps:

- Include modeling of the current PAX Tax / Trust Fund economic dynamics explicitly in IP behavior, to obtain even more realistic behavioral simulation for the IP.
- Examine enroute capacity enhancements

D. Revolutionary Concept II- Service Provider Coordination

The next set of parameters investigated were those that defined the likelihood that the two different types of service providers would add links. Specifically, these are the probability of adding link if thresholds are met for both long-distance (**SPL3**) and regional service provider (**SP3R**). Once again the measures of goodness are the average node saturation and average clustering coefficient cluster coefficient, indicating delay and robustness measures respectively. This was run under Scenario 2. The results that display the patterns in behavior of the SPs under Scenario 2 are illustrated in Figure 17. In this case, patterns

observed indicate that when demand is more distributed, coordination between SP types can moderate saturation. It is difficult, however, to draw any further conclusions from the cluster coefficient response; clearly more study is needed in this case.

Interpretation of Concept Results:

- It appears that a similar add probability for each SP type results in low saturation and high average cluster coefficient – reduced delay and increased robustness
- The evolution in the rate of growth of Long SP and Regional SP has implications for fleet mix:
    - Greater distributed Ops by active regional SP means more smaller aircraft
    - More long point-to-point ops means more versatile large aircraft

Logical Next Steps:

- Explore variations in SP distance thresholds
- Explore strategies for managing or encouraging inter-SP operations
- Formal modeling of SP competition & cooperation (incentive-based logic)
- Extension to study of personal air vehicle operational scenario

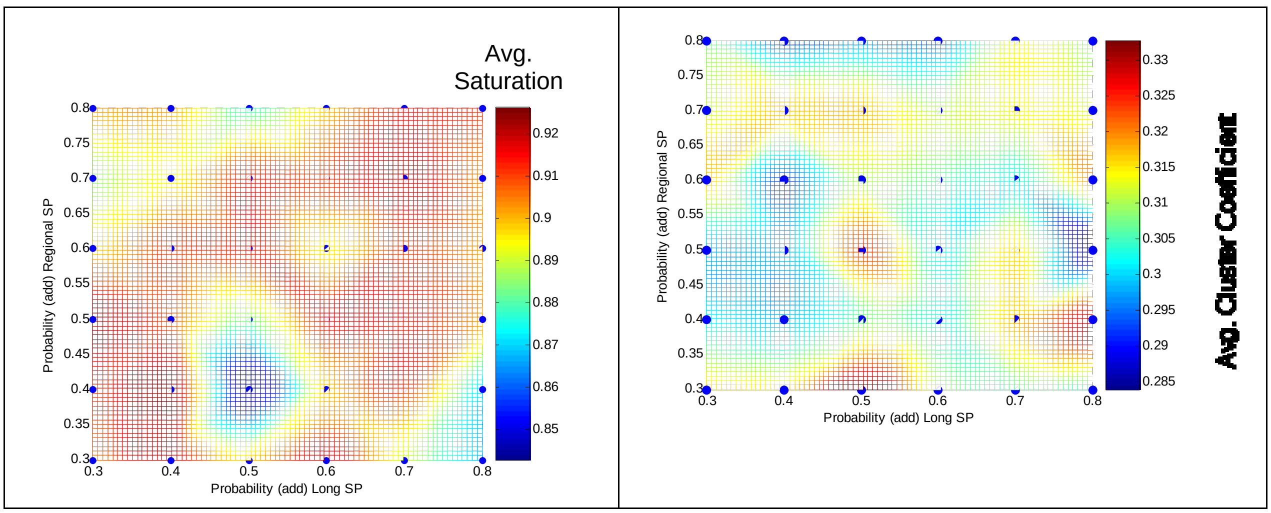


Figure 17: Simulation results for service provider coordination concept

VII. Summary and Future Work

A. Summary

The nature of the two concepts developed in this RSCA study share the same theme- the need for a “tunable NAS network”- in which the shape of the capacity network can be molded by the particular (but natural) behavior of service providers (SPs) and infrastructure providers (IPs) to drive the System-of-Systems towards scalability. For IPs, the ability to show agility in adding (or shifting) capacity is crucial. Reaction times must be within a certain proximity to the time-scale at which the network demand changes. For SPs, the potential for coordinated action for the betterment of the entire network appears promising. While the findings are the results of a “conceptual design process”, they can serve both NASA and the FAA by providing insight into which ratios of parameters are important in achieving sustainable transformation in a complex, evolving System-of-Systems such as the NAS. The System-of-Systems approach also appears to indeed provide a new “systems analysis” approach that may serve us well in the future.

B. Future work

Though illuminating results have been obtained in this RSCA study and portions of the analysis approach have been validated, many interesting questions remain. Answers to these questions are also very relevant to the transformation activities being undertaken by NASA and the FAA. A selected few of these questions are summarized below, chosen primarily because the analysis framework chosen for this study could have immediate use in addressing them.

Questions of optimal aircraft fleet mix:

- What is the optimal mix of new aircraft designs that provide maximum effectiveness in the networks that are likely to evolve?
- What are the non-traditional performance metrics that make aircraft more compatible with a tunable network?

In the language of the system-of-systems approach, aircraft represent a link in a capacity network topology and as a financial asset in the stakeholder value network topology. By understanding the requirements of the optimal networks, the requirements on aircraft design can be deduced through an optimization process.

Questions of optimal networks for measures beyond capacity and robustness- safety and environmental compatibility:

- What are challenges associated with an increasingly heterogeneous mixture of large and small aircraft?
- What are the limits of what's possible for high volume operations in a regional network?
- What are the environmental impacts of a more distributed network that may be required to enhance accessibility?

In this study, the measures obtained from topological analysis through Network Theory were mapped to NAS objectives like capacity and robustness. However, there are other measures of import that matter, such as safety (always the number one priority) and environmental impact. With the inclusion of models for these aspects, the clarity in determining truly optimal networks and rule sets can be obtained.

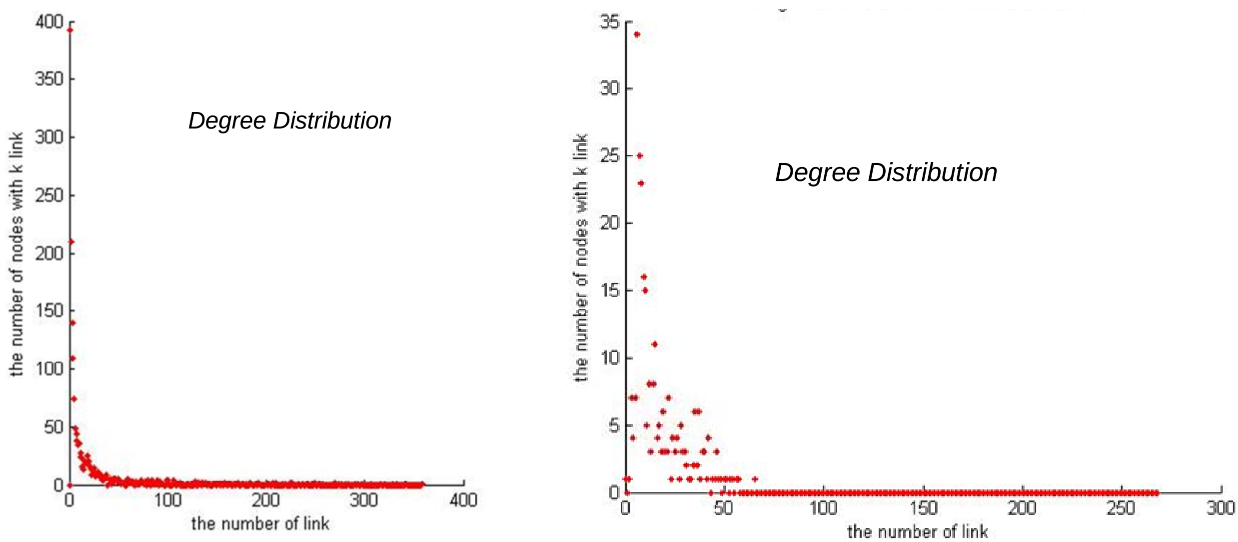
Questions of new business models and effects on NAS:

- What is the impact of shifting NAS networks on the current aviation trust fund paradigm?
- What are the possible reactions of hub-and-spoke carriers to the widespread onset of regional on-demand service providers and how would those reactions feedback to demand on the NAS?
- What are the implications of the growth of personal use aviation as transportation mode option?

The formulation employed in this RSCA study specifically accounts for the economic imperatives that drive many members of the stakeholder network. The questions listed here could be addressed with a more detailed formulation of the problems already study and documented in this report.

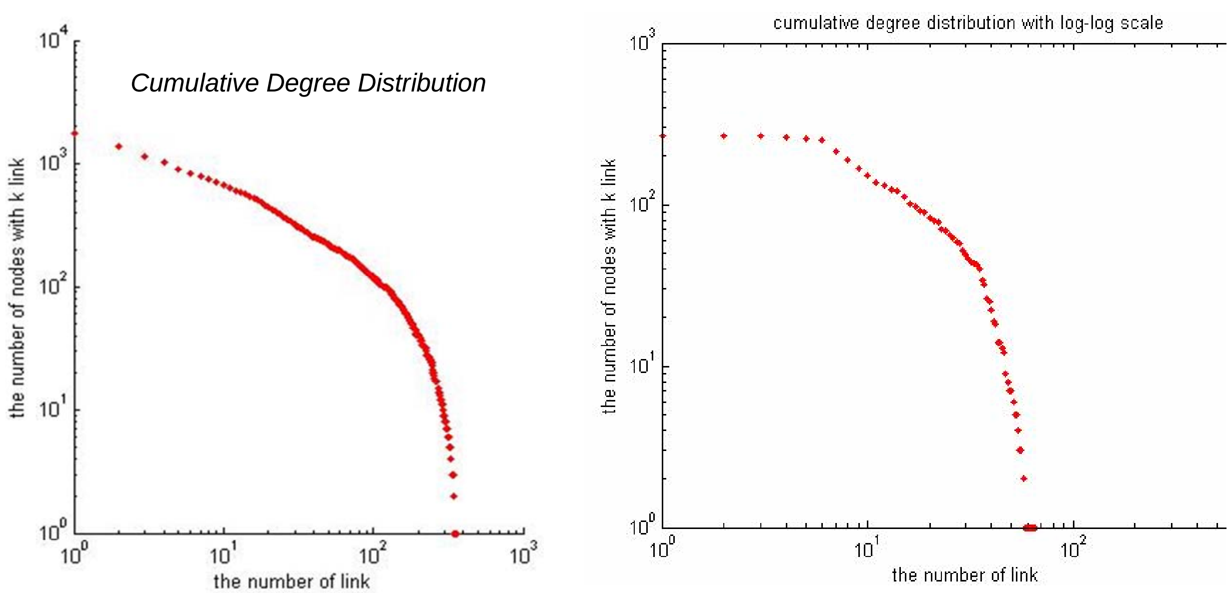
VIII. Appendix: Additional Validation of the NTSS

Although the NTSS model does not claim to capture all of the intricate behaviors in the NAS evolution, *it is important to understand whether NTSS results can capture within the collection of possible states the actual evolution we have seen in the past periods of the NAS.* The graphs displayed in Figure 18 and Figure 19 display results of a comparison between the actual network as analyzed empirically using 2004 BTS data and the network produced by the NTSS after starting it with a rough representation of the 1990 U.S. system (again from the BTS) and letting it evolve under the baseline settings to the 2004 state. The results indicate that the structure and behavior predicted by the NTSS is accurate, even though *NTSS* is smaller representation of real capacity network (indicated by increased scatter in the degree distribution and lower maximum degree in the cumulative distribution.



a) empirical degree distribution b) simulation degree distribution

Figure 18: Comparison of Degree Distributions: Empirical vs. Simulation



a) empirical cumulative degree distribution b) simulation cumulative degree distribution

Figure 19: Comparison of Cumulative Degree Distributions: Empirical vs. Simulation

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